Biodiversity Management and Stock Price Crash Risk

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Abstract

This study examines the relationship between corporate biodiversity management and financial risk. While the increasing loss of biodiversity and ecosystem services is seen as an important risk factor on a societal level, the financial consequences of these risks on a company level have thus far been neglected by empirical financial research. We posit that strong corporate actions towards preserving biodiversity reduces firms' financial risks. Using a global sample and novel data on firm's biodiversity management, our results show that companies with stronger structures, implementations, and actions on biodiversity management see a decline in stock price crash risk. In an additional analysis, we focus on environmental inspections as a possible way through which negative information on biodiversity management is released. Using a subsample of North American firms, we find that firms which see an inspection of their facilities see an increase in their stock price crash risk.

1 INTRODUCTION

Biodiversity loss and its consequences are currently recognized as one of the most urgent risks the world is currently facing (WEF, 2022). Therefore, the objective of this study is to investigate whether financial markets are aware of the biodiversity risks that companies face. In contrast to climate change, which receives significant attention from both investors and financial research (Krueger et al., 2020; Stroebel & Wurgler, 2021), biodiversity issues are not an area of importance for corporate reporting (Adler et al., 2017; Adler et al., 2018), their financial decisions (Nedopil, 2022), or their overall sustainability practices (Schaltegger et al., 2022). This is despite the fact that an estimated 20 percent of the largest publicly traded companies have material risks associated with biodiversity loss and its impacts (Carvalho et al., 2022). Rather, companies causing significant negative impacts on biodiversity, such as mining, adopt reporting techniques to dilute or play down their negative impacts (Boiral, 2016). Meanwhile, there has been a substantial increase in large publicly traded companies emphasizing their commitment to biodiversity conservation (29 percent of the largest publicly traded companies in 2018), in particular among companies that are more dependent on or have a greater impact on ecosystem services (Carvalho et al., 2022).

The surveys by Krueger et al. (2020) and Stroebel and Wurgler (2021) show that most institutional investors evaluate climate risks as a material risk factor. For instance, climate risks significantly increase a company's credit default swap (CDS) or bond spreads, both measures for an increased company's risk profile (Kölbel et al., 2020; Seltzer et al., 2022). In contrast to climate change risks, biodiversity risks are harder to grasp due to their high complexity (Schaltegger et al., 2022). Efficient corporate environmental management (i.e., strong environmental performance) mitigates perceived corporate risk by investors and hedges against climate-related risks (El Ghoul et al., 2018; Y. Kim et al., 2014). In analogy, we argue that strong biodiversity management is negatively associated with financial risk.

We hypothesize that, due to distinct features of biodiversity risks, strong biodiversity management affects financial risk perceptions. To our knowledge, there is no study to date that addresses the (non)importance of biodiversity risk and its management as a financial risk factor. Thus, this paper is the first to empirically analyze the relationship between a company's actions on reducing its impacts and dependencies on biodiversity and financial risk. We capture financial risk by stock price crash risk, a frequently applied measure to assess the risk of substantial negative stock returns (Habib et al., 2018). In a multivariate analysis, we study whether strong biodiversity management is acknowledged as value preserving by financial markets and whether it can help reduce a company's risk profile. To measure biodiversity management, we use data from Vigeo Eiris, a subsidiary of the rating agency Moody's. Vigeo Eiris is one of the few data providers collecting yearly data on corporate biodiversity management. Drawing on a global dataset across 45 countries of 1,402 listed firms, our results indicate that companies with stronger biodiversity management experience a lower risk of significant stock price declines. We use a global dataset as the loss of biodiversity affects companies worldwide. Our results show that the management of biodiversity impacts and dependencies thereof has an important influence on the perception of firms' financial risks, besides overall environmental, social, and governance (ESG) performance. A one standard deviation increase in overall biodiversity management is associated with a decrease of 4.2393 percent and 5.0388 percent for our two measures of stock price crash risk. Moreover, we find that stakeholder feedback on firms' biodiversity management is of special importance for firms in need of legitimacy, i.e. those with low overall ESG performance or low profitability.

In an additional analysis, we look at environmental inspections by the EPA, the US Environmental Protection Agency, as an exogenous shock to the information environment regarding the state of a firm's biodiversity management. In a difference-in-differences design, we find that firms that are subject to an EPA inspection see a significant increase in their stock price crash risk in the year following the inspection. This underlines that a firm's impact on the state of biodiversity around its operating facilities is a potential financial risk factor. We argue that environmental inspections are one channel through which negative information on companies' biodiversity stewardship is revealed to the public.

The contribution of our study is twofold. First, it enhances our understanding of the importance of environmental risk factors for financial markets besides climate change. While climate change and its consequences are currently getting a lot of attention (Giglio et al., 2021; H. Hong et al., 2020), this study underlines that specific environmental risks should not be limited to this one topic. Prior research so far examines how companies value biodiversity itself (Anthony & Morrison-Saunders, 2022), the extent to which they report on biodiversity (Hassan et al., 2022), their commitment to biodiversity (Silva et al., 2019), and the factors that motivate companies to disclose on biodiversity (Hassan et al., 2020). Moreover, Carvalho et al. (2022) finds that companies exposed to biodiversity-related risks implement policies for biodiversity. Thus, our findings extend these studies on the importance of biodiversity management in financial decision making. By examining the financial consequences of biodiversity management, we open a new strand in the biodiversity disclosure and management literature, which has mainly focuses on the importance and determinants of biodiversity disclosure (Boiral & Heras-Saizarbitoria, 2017a, 2017b).

Second, this study adds to the literature analyzing how non-financial risk factors influence stock price crash risk. Most of these studies focus only on a subset of industries such as banking or renewable energy (Fiordelisi et al., 2022; Yildiz & Karan, 2020). In contrast, our sample includes a wide range of different industries across multiple countries, all of which have varying relationships and dependencies towards biodiversity. Finally, our study has practical implications for management and investors, as we show that shareholders value the management of biodiversity risks, suggesting that the impacts and dependencies on (intact) ecosystems are a risk factor to consider. Thus, companies should allocate sufficient resources to manage biodiversity risks in order to prevent declines in share price.

The remainder of the paper is structured as follows. The next section reviews prior literature and develops our hypotheses. Section 3 presents our methodology and the sample selection procedure. We provide and discuss the results in Section 4. Section 5 displays additional results and robustness checks. Section 6 concludes.

2 HYPOTHESES DEVELOPMENT

2.1 Biodiversity Loss and Firm Level Risk

Studies by Dasgupta (2021) and Carvalho et al. (2022) show that the loss of biodiversity poses a significant risk for many companies. Up to now, empirical financial research has not examined the importance of biodiversity (loss) for corporations and its trait as a possible financial risk factor on a firm level. A few studies point out the great variety to which companies report on biodiversity issues (Adler et al., 2017; Adler et al., 2018; Anthony & Morrison-Saunders, 2022), underlining that the attitude of companies towards biodiversity is heterogeneous. These findings are supported by the survey results of Wagner (2022), suggesting that the majority of corporate actions toward safeguarding biodiversity are of symbolic value. Contrary to climate change, biodiversity impacts, dependencies, and actions are harder to grasp and evaluate in corporate reporting due to their high complexity (Schaltegger et al., 2022). Hence, no unifying variable to measure and manage related risks, such as CO_2 emissions (Kennedy et al., 2022), or clear thresholds for intactness exist (Addison et al., 2020).

Nature-related risks, such as the risks arising from biodiversity loss, are distinct from the non-financial risk factors analyzed by prior literature. Most importantly, they depict salient, yet large scale issues. In his assessment of the economics of biodiversity, Dasgupta (2021) defines three nature-related financial risks: physical risks, transition risks, and litigation risks. Firms might be exposed to one, two, or all three of these risks. On the one hand, many firms are dependent on various types of ecosystem services.[1] For instance, chemical or energy firms

[1] The IBPES (2022) defines ecosystem services as "the benefits people obtain from ecosystems".

might require functioning rivers for cooling their operations, and agricultural firms rely on insects such as bees for the pollination of their crops (*physical risks*). On the other hand, firms are putting pressure on the state of biodiversity through their business operations. For example, mining firms might need to destroy a once thriving area (in terms of biodiversity) to extract resources. Firms might thus be under pressure from civil society or regulatory authorities, i.e., through litigation (*litigation risk*) or through emerging regulation (*transition risks*). This could have various negative consequences, such as threatening a firm's reputation, putting the firm at risk of paying compensation for the damage caused, or even jeopardizing the current business model through legislation. These three types of risks all have distinct negative consequences for a firm's financial position and might lead to an unexpected decline in shareholder value and can thus be considered a financial risk for many companies.

2.2 Stock Price Crash Risk and Biodiversity Management

A multitude of studies analyze factors influencing a firm's stock price crash risk, such as tax avoidance (J.-B. Kim et al., 2011), religion (Callen & Fang, 2015), or CEO age (Andreou et al., 2017). Joseph Chen et al. (2001) conduct the first empirical analysis and find that certain firms, i.e. those who see an increase in trading volume in their common stock, are more likely to be subject to a stock price crash. Besides financial variables influencing a firm's stock price crash risk, non-financial topics are of increasing importance for companies. In their analysis, Y. Kim et al. (2014) find that a firm's ESG performance mitigates stock price crash risk. They attribute this finding to less bad news hoarding by firms with strong ESG performance. Recently, other non-financial risk factors have been examined regarding their influence on stock price crash risk. Yildiz and Karan (2020) find that a country's overall culture towards environmental issues is a predictor of stock price crash risk. The study by Minnick et al. (2022) shows that carbon risk, measured by a firm's total CO_2 emissions, is a factor driving a firm's stock price crash risk. This relationship is attenuated by factors such as the quality of governance or the presence of institutional investors. Yet, non-financial performance is a wide field that goes far beyond climate change risks (measured by CO_2 emissions). In addition, aggregated sustainability performance might not be able to capture all subtopics of potential importance for financial markets. One further factor to consider might be a company's action toward safeguarding biodiversity.

Corporations focusing on managing their impacts and dependencies on biodiversity are indicating that they value intact ecosystems and biodiversity. It signals that they are actively managing the pressures their operations present to biodiversity as well as their dependency on well-functioning ecosystems. These firms intend to reduce their biodiversity risks and thus, we assume, their stock price crash risk. This hypothesis is in line with Christensen (2016), who finds that the negative outfall of non-financial misconduct can be mitigated by firms through disclosure of their ESG activities. Considering the previous literature on stock price crash risk and the distinct properties of biodiversity risks, we posit that stronger biodiversity management decreases stock price crash risk. Hence, we state our first research hypothesis as follows:

Hypothesis 1 (H1). *Strong biodiversity management negatively influences a firm's perceived risk (i.e., stock price crash risk).*

2.3 Stakeholder Response to Biodiversity Management and Legitimacy

While overall biodiversity management directly reduces a firm's risk profile, the response by stakeholders to a firms' management and actions towards biodiversity might additionally be of importance to form their exposure of risk (i.e., stock price crash risk). Chiu and Sharfman (2011) show that the visibility of corporate actions to stakeholders is a channel through which firms' legitimacy is influenced. One important reason companies undertake ESG activities is to gain and retain legitimacy. In turn, increased legitimacy has positive financial consequences (Chiu & Sharfman, 2011; Kölbel et al., 2020). If firms fall short in overall ESG performance, they might opt for other possibilities to enhance their legitimacy. In such cases, positive stakeholder feedback on biodiversity management and actions might provide a fall-back option for those companies. Thus, we hypothesize that stakeholder feedback in response to biodiversity management and activities influences a firm's legitimacy and hereby its financial risk (i.e. stock price crash risk). Yet, as biodiversity is only gradually gaining the attention of companies and investors (Adler et al., 2018), we hypothesize that stakeholder feedback to biodiversity management and activities is not of general importance but only for those firms which lack legitimacy in other dimensions (i.e., showing a low overall ESG performance). Thus, we state our second research hypothesis as follows:

Hypothesis 2 (H2). *Stakeholder feedback on biodiversity management reduces shareholder risk perceptions (i.e., negatively influences stock price crash risk) only for companies that have a need for legitimacy.*

3 METHODOLOGY

3.1 Measuring Stock Price Crash Risk

To calculate measures of stock price crash risk, we follow J.-B. Kim et al. (2021) and start by estimating the following regression to estimate firm-specific weekly stock returns:

$$r_{i,\tau} = \alpha_i + \beta_1 r_{m,\tau-2} + \beta_2 r_{m,\tau-1} + \beta_3 r_{m,\tau} + \beta_4 r_{m,\tau+1} + \beta_5 r_{m,\tau+2} + \epsilon_{i,\tau} \tag{1}$$

Where $r_{i,\tau}$ depicts the return for firm i during week τ. $r_{m,\tau}$ depicts the market return for week τ. Moreover, we include the market returns two weeks around each week to control for nonsynchronous trading (Dimson, 1979; J.-B. Kim et al., 2021), using the country specific MSCI index return as a proxy for local market returns. We then define a firm's weekly stock return $W_{i,\tau}$, calculated as the natural logarithm of one plus the residual from Equation 1. Following the comprehensive literature on stock price crash risk (Hasan et al., 2021; H. A. Hong et al., 2017; J.-B. Kim et al., 2021), we use two measures for crash risk. The first one, $NCSKEW$ is the negative conditional return skewness, whereas the second, $DUVOL$, captures the down to up volatility. $NCSKEW$, first introduced by Joseph Chen et al. (2001), is calculated using the negative third moment of a firm's weekly returns during a year and then dividing it by the standard deviation of weekly returns, raised to the third power. We define $NCSKEW$ in Equation 2. $DUVOL$ states asymmetric volatilities by dividing the sum of a firm's squared weekly stock return $W_{i,\tau}$ in down weeks by the sum of all squared weekly returns in up weeks, as defined in Equation 3. Following Joseph Chen et al. (2001), we define up (down) weeks as those weeks, in which the return is greater (smaller) than a firm's average weekly return in the corresponding year. n_u and n_d respectively, depict the number of up and down weeks within a firm-year. For both variables, higher values indicate higher risk of a stock price crash.

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{3/2}} \tag{2}$$

$$DUVOL_{i,t} = \ln\left[\frac{(n_u-1)\sum_{DOWN} W_{i,t}^2}{(n_d-1)\sum_{UP} W_{i,t}^2}\right] \tag{3}$$

3.2 Empirical Model

We deploy the following regression to test our main hypothesis on the relationship between stock price crash risk and a firm's biodiversity management:

$$\begin{aligned} CRASH_{i,t} = {} & \alpha + \beta_1 BIODIV_{i,t-1} + \sum_{k=2}^{K} \beta_k \, CONTROLS_{k,i,t-1} \\ & + \sum_{c=1}^{C} \tau_c \, Country_{c,i} + \sum_{j=1}^{J} \tau_j \, Industry_{j,i} + \sum_{t=1}^{T} \psi_t \, Year_t + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $CRASH_{i,t}$ depicts one of the two measures of stock price crash risk, $NCSKEW_{j,t}$ or $DUVOL_{j,t}$ $BIODIV_{i,t-1}$ depicts our main variable of interest, indicating a firm's overall biodiversity management in the previous year. The overall biodiversity management variable is calculated by averaging all of the three biodiversity subscores provided by Vigeo Eiris. We use the subscores as further variables of interest. First, *Biodiv. Leadership* proxies a firm's overall commitment towards preserving biodiversity indicating for example the existence of clear policies related to the topic and the public visibility thereof. Second, *Biodiv. Implementation* indicates the state of overall implementation of said commitment. The pillar assesses the means allocated to achieving the commitment and the scope of implementation in both geographical as well as operating segments. Finally, *Biodiv. Results* evaluates the results of a firm's ambitions, looking at stakeholder feedback or biodiversity measures. Each of the three biodiversity scores ranges between 0 and 100, with higher values indicating stronger performance. See the studies by Bilbao-Terol et al. (2019) and Cavaco et al. (2020) for a more detailed description of the three-pillar structure established by Vigeo Eiris.

Additionally, we follow J.-B. Kim et al. (2021) and include several control variables that the prior literature identifies to be determinants of stock price crash risk. We include the lagged negative skewness of stock returns (*LAGNCSKEW*), detrended trading volume (*DTURNOVER*), and the standard deviation of weekly returns (*SIGMA*). Furthermore, we include several control variables based on company fundamentals. These are firm size (*SIZE*), market to book ratio (*MB*), leverage (*LEV*), and return on assets (*ROA*). We follow the approach by H. A. Hong et al. (2017) to control for opaqueness (*OPAQUE*). We retrieve all data for stock prices as well as control variables from Refinitiv Datastream. As our sample consists of a global sample of companies from different countries, we convert all currency amounts into USD. As a final control variable, we include a firm's ESG performance (*ESG*) using Refinitiv ESG data to ensure that the biodiversity variable is not merely a proxy for a firm's overall ESG performance, which Y. Kim et al. (2014) find to be another determinant of stock price crash risk. We winsorize all control variables at the top and bottom 1 percent level to reduce the possible impact of outliers.[2] Further, we include country and industry fixed effects to control for time invariant specific factors. We include year fixed effects to account for temporal events. See Table 1 for a detailed overview of the variables included in our analysis.

(Insert Table 1 around here)

[2] In untabulated analysis, we find that the results are qualitatively similar if we do not winsorize our control variables.

3.3 Sample Selection and Descriptive Statistics

Our sample starts with all companies covered by the Vigeo Eiris biodiversity score worldwide. Vigeo Eiris, a subsidiary of Moody's, is one of the few providers of firm-level biodiversity information. Due to a strong uptake in firms with available data on biodiversity management, we start our sample period in 2009. Overall, our sample covers a time period of 13 years, ending in 2021. We begin with a total of 12,483 observations from 2,230 unique companies. After excluding companies with missing stock price data, missing controls and ESG variables, the sample includes 7,161 observations from 1,402 companies across 45 different countries. Table 2 provides detailed steps of the sample selection procedure.

Table 3 gives an overview of the distribution of companies across industries (Panel A) and countries (Panel B) included in our sample. Around 18 percent (257 firms) of the companies included in our sample are headquartered in the US, followed by Australia and the United Kingdom with both around 8.2 percent (115 and 114 firms, respectively). Other countries with a high number of companies include Canada (108 firms), Japan (81 firms), and Hong Kong (64 firms).

(Insert Tables 2 and 3 around here)

Tables 4 and 5, respectively, display the summary statistics and pairwise correlation coefficients of the variables used in the baseline analysis. The control variables are generally of similar size and standard deviation compared to other studies on stock price crash risk (Y. Kim et al., 2014; J.-B. Kim et al., 2021). Our size variable is larger than in other studies analyzing factors influencing stock price crash risk, with a mean market capitalization of 6.7 billion USD. We attribute this to our measure for biodiversity management only being available for large companies. This is in line with other studies employing ESG data (Yildiz & Karan, 2020), as data providers of ESG data frequently focus their attention toward companies with high market capitalization. The average firm shows a market-to-book ratio of 1.82 and a return on assets of 4 percent. The correlation coefficients between our different (sub)scores of biodiversity management are, except for the variable measuring the stakeholder response to biodiversity actions (*Biodiversity Results*), highly correlated with correlation coefficients ranging between 0.64 and 0.88 and statistically significant at the 5 percent level.

(Insert Tables 4 and 5 around here)

4 RESULTS

4.1 Biodiversity Management and Stock Price Crash Risk

Tables 6 and 7 depict the regression results of Equation 4 for the two measurements of stock price crash risk (i.e., *DUVOL* and *NCSKEW*). For all our regressions, we report clustered standard errors by firm-level in parentheses below each coefficient. Column 1 in Table 6 (Table 7) indicates that overall strong biodiversity management is related to a lower stock price crash risk with a coefficient of −0.0017 for *DUVOL* (−0.0027 for *NCSKEW*), statistically significant at the 1 percent level. Both effects are statistically and economically significant. On average, a one standard deviation increase in overall biodiversity management is associated with a decrease of 4.2393 percent in *DUVOL* in the following year.[3] The effect size for *NCSKEW* is of similar magnitude (−5.0388 percent). These results suggest an economically significant negative relationship between biodiversity management and stock price crash risk, supporting our Hypothesis 1. The coefficients of our control variables are in line with other studies in terms of sign and magnitude (Jun Chen et al., 2017; Y. Kim et al., 2014; J.-B. Kim et al., 2021). Firms that show higher past returns, greater size, and exhibit a higher return on assets are linked to higher crash risk.

Columns 2 to column 5 in Table 6 (Table 7) show the results for each of the three subscores of biodiversity management separately. The coefficients on the two subscores indicating *Biodiv. Leadership* and *Biodiv. Implementation* are of the same sign and similar magnitude as the overall biodiversity management variable and are at least statistically significant at the 5 percent

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[3] For *Biodiversity*, we obtain the effect size as follows: $\frac{\beta_{Biodiversity} * SD_{Biodiversity}}{SD_{DUVOL}}$, hence: $\frac{-0.0017*19.3809}{0.7772} = -4.22$ percent.

level. Interestingly, the coefficient for the *Biodiv. Results* variable, capturing the response of stakeholders, shows no statistical significance at frequently used levels. This provides initial evidence for our Hypothesis 2, indicating that positive stakeholder feedback does not result in a general reduction in stock price crash risk.

(Insert Tables 6 and 7 around here)

4.2 Stakeholder Response to Biodiversity Management and Legitimacy

To test the conditioned relationship between *Biodiv. Results* and stock price crash risk, we turn to an analysis using interaction terms. We calculate interaction terms between the *Biodiv. Results* variable and a set of variables capturing a company's requirement to establish legitimacy. We consider three different dimensions that may have an impact on the need for organizations to establish or maintain their legitimacy. First, if they have weak biodiversity management and implementation, Second, if they have overall weak ESG performance. Third, if they exhibit poor financial performance. Hence, we first include the two other subscores for biodiversity as moderators, as good performance regarding *Biodiv. Results* (i.e., positive stakeholder feedback) might only be of importance for a subgroup of firms (i.e. those with low implementation of their actions towards biodiversity). To capture overall ESG performance, we include the overall ESG score. In the case of weak overall ESG performance, stakeholder feedback for certain topics (e.g. biodiversity) may gain importance. The same applies to financial performance, which we capture with a proxy for profitability, the return on assets.

For the analysis, we calculate the interactions between *Biodiv. Results* and a set of dummy variables. The dummy variable (i.e., *Low Biodiv. Leadership*) is equal to one if the value for the variable (i.e., *Biodiv. Leadership*) is smaller than the corresponding sample median, zero otherwise.[4] We use this approach for all interaction terms accordingly.

(Insert Table 8 around here)

[4] Again, note that the results are qualitatively unchanged if we form the two groups based on yearly median values (untabulated).

Table 8, columns 1 to 4 regress our two measures of stock price crash risk on interaction terms between *Biodiv. Results* and dummy variables derived from the two other subscores of biodiversity management. None of the four interaction terms is statistically significant at the 10 percent level or lower, indicating that stakeholder feedback is not more important for firms with low biodiversity management (implementation). Columns 5 to 8 show that the interaction terms between *Biodiv. Results* and *ROA* (*ESG*) are negative and statistically significant at the 10 percent (5 percent) level. This indicates that strong performance regarding *Biodiv. Results* (i.e., good stakeholder feedback) is of special importance to the financial risk position of firms with low financial (ESG) performance. Firms with low ESG performance might derive a high marginal utility from good biodiversity management as they do not benefit from the risk reducing effects of strong ESG performance (Godfrey et al., 2009; Y. Kim et al., 2014). Similarly, firms with low financial performance (i.e., low return on assets) might focus on strong management of biodiversity to gain or maintain their legitimacy. Overall, the results provide support for our Hypothesis 2.

5 ADDITIONAL ANALYSIS

5.1 Environmental Inspections and Stock Price Crash Risk

Building on the above results indicating that biodiversity management reduces the risk of sudden stock price declines, we attempt to establish a causal relationship in this section. Following agency theory (Jensen & Meckling, 1976), the majority of studies on stock price crash risk attribute the occurrence of a sudden drop in share price primarily to bad news hoarding as a consequence of failure of corporate governance mechanisms (Hutton et al., 2009). These failures lead to an asymmetric information environment between management and outside stakeholders. In such a case, managers may withhold negative information through reduced transparency for personal benefits, such as empire building or higher compensation (Ball, 2009; Graham et al., 2005). Negative information stockpiles and is eventually released all at once after the management is no longer able to withhold it (J.-B. Kim et al., 2021). This revelation of bad news is then the trigger for a sudden decline in share price, a stock price crash. Emerging areas of importance for companies, such as ESG issues, are a particular area of high information asymmetry, as they frequently do not yet have established and standardized disclosure practices (Schiemann & Sakhel, 2019). Particularly, corporate reporting on biodiversity issues is one of these emerging topics. Several studies analyze firms' disclosure and find that even the world's largest companies or those operating in industries with high impacts or dependencies on biodiversity, such as mining, only provide limited information on biodiversity risks (Adler et al., 2018; Boiral, 2016; Hassan et al., 2020; Rimmel & Jonäll, 2013). Due to the high information asymmetry between managers and outside stakeholders, this opaque environment is well suited for the hoarding of negative information related to biodiversity and ecosystem services.

Besides transparency towards these issues, such as through strong biodiversity management, one possible factor attenuating the extent of information asymmetry are functioning internal and external control mechanisms. Prior studies show that internal and external controls have distinct influence on the information environment and subsequent stock price crash risk (Jun Chen et al., 2017; J.-B. Kim et al., 2011; J.-B. Kim et al., 2020). Especially inspections carried out by governmental agencies might detect the existence of bad information within a company (Zhang et al., 2021), leading to a subsequent release of this news and a corresponding reaction from shareholders.

In consequence, we analyze whether environmental inspections of corporate facilities are one of the channels through which stockpiled bad news is uncovered and subsequently made public. For the analysis, we focus on firms within the US as we require data from the EPA. This is a federal agency charged, among other tasks, with the oversight of the compliance of possibly polluting facilities operated across the US. The EPA publishes extensive data on these polluting facilities and whether the EPA conducted an inspection.[5] Additionally, we keep Canadian firms, as they also frequently operate facilities in the neighboring US. Overall, the EPA lists 62,048 facilities with a valid id out of which the majority (41,426) were at least once subject to an inspection. It is noteworthy that the EPA only publishes the date of the most recent inspection for each facility.[6] Thus, it is not possible to identify whether a facility was subject to a prior inspection. To mitigate this shortcoming, we aggregate the data on a firm level and use the earliest year any facility of one of the sample companies was subject to an EPA inspection as a treatment for the release of negative information on biodiversity management to the stock market. Moreover, the omission of inspections prior to the most recent inspections on a facility level only works against us finding any results as negative biodiversity information might have been revealed through the earlier inspection, reducing the effect of the latter. As only a small subset of facilities is inspected by the EPA each year, inspections come as a surprise for investors. Thus, we use the event of an environmental inspection as a quasi-natural experiment where some of our sample companies receive a treatment. Overall, the sample for the difference-in-differences analysis includes 1,701 observations and 365 unique firms which were subject to a total of 704 inspections between 2010 and 2021. While our dataset for the baseline analysis starts in 2009, we only consider inspections starting in 2010 as we require one prior year without any inspection for propensity score matching. As only a minority of firms were subject to inspections (we identify a total of 57 companies as treated firms), we use a propensity score matching approach to create a balanced sample of treatment and control firms. We match treatment and control firms using a logit model with a binary variable equal to one for treated firms and equal to zero for control firms as dependent variable and a firm's leverage and past stock returns as independent variable to find the closest match in terms of financial health. We

[5] See the study by S.-H. Kim (2015) who uses EPA inspections in their study for a detailed description of the EPA processes.
[6] For more information on the EPA's inspection guidelines and procedures, please see https://www.epa.gov/enforcement/federal-facilities-inspections-guide-epas-access-and-inspection-authorities.

use data one year prior to the first inspection year for the matching approach (Caliendo & Kopeinig, 2008). After matching each treated firm to a corresponding control firm, we use a 3-year period around each treatment (i.e., first time inspection) to analyze the effect of EPA inspections on stock price crash risk. Due to data restrictions for either treated or control firms, the difference-in-differences sample includes 301 observations (instead of the expected 342).

Table 9 depicts the sample means for the difference-in-differences sample split across the assignment to treatment or control group one year prior to each treatment. As indicated by the results of a t-test in the outright column, the majority of means of the control variables do not differ across the two groups, which indicates a good fit for our matching approach.

The variable of interest in a difference-in-differences regression is the interaction term *Treat∗Post*, which is equal to one for treated firms in the years subsequent to the treatment (in this case, the first EPA inspection), and zero for all other observations. Table 10 contains the results of the difference-in-differences regression on the two measurements of stock price crash risk. We include all control variables used in our main analysis.[7] As expected, the interaction term is positive and statistically significant, indicating that EPA inspections increase a firm's stock price crash risk, likely through the revelation of negative information on a firm's biodiversity activities.

(Insert Tables 9 and 10 around here)

5.2 Industry-level Risk

The fallout arising from biodiversity loss and lapse of ecosystem services is not evenly distributed across industries. Primary industries, i.e. those which directly rely on natural resources as input for their production processes, are much more at risk than secondary industries with less direct overlap with nature (Carvalho et al., 2022; Wagner, 2022). We thus turn to an analysis, where we differentiate firms by their exposure to biodiversity risks by

[7] Note that we do not include country fixed effects as the sample for the difference-in-differences design only includes companies from two countries. The results remain unchanged if we include country fixed effects for the analysis.

following the approach of Rimmel and Jonäll (2013) and Adler et al. (2018). Both studies rely on the classification approach by F&C Asset Management (2004) into industries with red (high), amber (medium), and green (low) risks regarding biodiversity. We assign a dummy variable a value of one if a company is considered to be active in a red industry.[8] Overall, around 62 percent (4,446) companies are operating in industries with high biodiversity risks. Table 11 presents the results. The interaction terms on the overall measure of biodiversity management are only statistically significant for the *DUVOL* measure. Thus, the results only show weak indication of biodiversity management being of greater importance for the financial risk of companies operating in high risk industries. Only the interaction term derived from *Biodiv. Implementation* and the dummy variable indicating high risk industries seem to positively influence a firm's stock price crash risk across our two measures of stock price crash risk. This indicates that the risk-reducing effect of strong *Biodiv. Implementation* is less pronounced for firms operating in high risk
industries.

(Insert Table 11 around here)

5.3 Robustness Tests

In this section, we perform a battery of robustness tests (untabulated, tables are available on request) to provide further support to our results. Table 5 shows high correlation coefficients between our control variable capturing overall ESG performance and our measures for biodiversity management. Correlation ranges between 0.51 for the overall measure of biodiversity management and 0.50 (0.48) for the variable indicating biodiversity leadership (implementation). To rule out that this correlation influences our findings, we rerun our regressions without controlling for overall ESG performance. Our results show, that the

[8] Note that F&C Asset Management (2004) uses the FTSE industry classification, whereas we use the industry classification provided by Vigeo Eiris, see Panel B of Table 3. Specifically, we set the dummy variable for a company equal to one if it is active in one of the following industries: Heavy Construction, Electric & Gas Utilities, Food, Forest Products & Paper, Hotel, Leisure Goods & Services, Mining & Metals, Oil Equipment & Services, Waste & Water Utilities, Energy

coefficients for our variables of interest remain unchanged in terms of magnitude and statistical significance, giving further support to Hypothesis 1.[9]

Second, we tackle the concern that overall biodiversity management might simply be a proxy of (i.e., highly correlated to) a company's overall disclosure quality or its awareness toward emerging ESG issues. As the issue of biodiversity loss is currently not of importance for many companies, firms with strong biodiversity management might simply be those which show high awareness of overall ESG issues and potentially drive our results. To alleviate this concern, we add a further control variable on companies' awareness of ESG issues. We retrieve information on whether companies have policies in place to address ESG issues, using data from Refinitiv. Overall, we collect information on 17 different ESG topics.[10] From this data, we construct a variable depicting the share of sustainability policies a firm has in place (i.e., if a company has policies for all 17 topics the variable is equal to 1, if the company has no policies in place the variable is equal to 0). We lose 293 observations compared to the baseline sample for which Refinitiv does not provide information on ESG policies. We add the variable as an additional control to our baseline regression and find that our results remain unchanged. This further strengthens our results by providing evidence that our variable on biodiversity management does not merely measure a company's overall awareness of emerging ESG issues.

6 CONCLUSION

The economic value of ecosystem services provided by intact biodiversity is undisputed on a societal level (Dasgupta, 2021). Capturing perceived financial risk by stock price crash risk, this paper looks at the importance of biodiversity management on a firm level. We construct a global sample of listed companies and find that strong biodiversity management decreases stock

[9] The only two submetrics related to biodiversity included in the calculation of the Refinitiv ESG score are the items ENERDP019 and ENPIO10V. Both are yes/no questions and only constitute to the overall ESG score to a very limited extent.

[10] Following the classification of ESG topics by Christensen (2016), we collect the following variables (Refinitiv codes in brackets): Society (SOCODP0067, SOCODP0066, SOCODP0069), product responsibility (SOPRDP0121, SOPRDP0124, SOPRDP0126, SOPRDP0128), labor (SODODP0081, SOHSD01V, SOTDD01V), human rights (SOHRD01V), environment (ENERDP0051, ENRRD01V, ENRRDP0121, ENRRDP0122, ENRRDP0124, ENRRDP0125).

price crash risk. In our analysis, we control for a multitude of different variables which prior literature finds to be determinants of crash risk and deploy several robustness checks to strengthen our findings. Thereafter, we use interaction analysis to test which set of companies stakeholder feedback toward biodiversity management and actions is of importance. We find that those firms that are in the need to build and maintain legitimacy, i.e. those with low overall ESG performance and low profitability, see a decrease in their stock price crash risk through better stakeholder feedback on their biodiversity management and activities.

One step further, we use environmental inspections by the EPA as quasi-natural experiments which we hypothesize to serve as a channel for the revelation of negative information on biodiversity management. A difference-in-differences regression on a propensity score matched sample shows which firms which are subject to an inspection by the EPA see an increase in their stock price crash risk. The results suggest a causal effect of biodiversity management on stock price crash risk, further supporting our main results.

Our paper contributes to our understanding of how non-financial risk factors influence companies' financial risks, adding to studies by Y. Kim et al. (2014) and Zhang et al. (2021). Moreover, our results guide corporate management by showing the importance of allocating sufficient resources towards actions preserving biodiversity to reduce a firm's financial risk. Companies should proactively approach emerging issues in order to avoid negative financial consequences for abstaining from action.

This paper has several limitations. Most importantly, we are not able to apply firm fixed effects due to a low variation of our variables of interest within firms. Incorporating firm fixed effects would capture time invariant firm characteristics and would provide further support to our results. The median (mean) standard deviation of our *Biodiversity* variable within firms is equal to 5.8189 (6.4733), which is substantially lower than the standard deviation across our whole sample. The low standard deviation indicates that biodiversity management is rather consistent across time on a firm level. However, we use a high number of control variables in addition to industry and year fixed effects to alleviate this concern as much as possible. One further caveat of this paper is that we rely on third-party data to measure biodiversity management. The factors influencing biodiversity degradation and how companies put pressure on local and global biodiversity are inherently complex and difficult to measure (Schaltegger et al., 2022). A high complexity is put up as one of the reasons why companies' responses to the loss in biodiversity has thus far been considered heterogeneous and often only of symbolic value. With no good indicator to measure a company's impact on biodiversity (compared to CO_2 emissions in the case of climate change), all existing variables are proxies at best. Future studies might use other indicators for corporate biodiversity management and the outcome thereof or develop new measurements themselves.

7 References

Addison, P. F., Stephenson, P. J., Bull, J. W., Carbone, G., Burgman, M., Burgass, M. J., Gerber, L. R., Howard, P., McCormick, N., McRae, L., Reuter, K. E., Starkey, M., & Milner-Gulland, E. J. (2020). Bringing sustainability to life: A framework to guide biodiversity indicator development for business performance management. *Business Strategy and the Environment*, *29*(8), 3303–3313. https://doi.org/10.1002/bse.2573

Adler, R., Mansi, M., & Pandey, R. (2018). Biodiversity and threatened species reporting by the top fortune global companies. *Accounting, Auditing & Accountability Journal*, *31*(3), 787–825. https://doi.org/10.1108/AAAJ-03-2016-2490

Adler, R., Mansi, M., Pandey, R., & Stringer, C. (2017). United nations decade on biodiversity: A study of the reporting practices of the Australian mining industry. *Accounting, Auditing & Accountability Journal*, *30*(8), 1711–1745. https://doi.org/10.1108/AAAJ-04-2015-2028

Andreou, P. C., Louca, C., & Petrou, A. P. (2017). CEO age and stock price crash risk. *Review of Finance*, *21*(3), 1287–1325. https://doi.org/10.1093/rof/rfw056

Anthony, S. J., & Morrison-Saunders, A. (2022). Analysing corporate forest disclosure: How does business value biodiversity? *Business Strategy and the Environment,* Article bse.3164. Advance online publication. https://doi.org/10.1002/bse.3164

Ball, R. (2009). Market and political/regulatory perspectives on the recent accounting scandals. *Journal of Accounting Research*, *47*(2), 277–323. https://doi.org/10.1111/j.1475-679X.2009.00325.x

Bilbao-Terol, A., Arenas-Parra, M., Alvarez-Otero, S., & Cañal-Fernández, V. (2019). Integrating corporate social responsibility and financial performance. *Management Decision*, *57*(2), 324–348. https://doi.org/10.1108/MD-03-2018-0290

Boiral, O. (2016). Accounting for the unaccountable: Biodiversity reporting and impression management. *Journal of Business Ethics*, *135*(4), 751–768. https://doi.org/10.1007/s10551-014-2497-9

Boiral, O., & Heras-Saizarbitoria, I. (2017a). Best practices for corporate commitment to biodiversity: An organizing framework from GRI reports. *Environmental Science & Policy*, *77*, 77–85. https://doi.org/10.1016/j.envsci.2017.07.012

Boiral, O., & Heras-Saizarbitoria, I. (2017b). Corporate commitment to biodiversity in mining and forestry: Identifying drivers from GRI reports. *Journal of Cleaner Production*, *162*, 153–161. https://doi.org/10.1016/j.jclepro.2017.06.037

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Callen, J. L., & Fang, X. (2015). Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis*, *50*(1-2), 169–195. https://doi.org/10.1017/S0022109015000046

Carvalho, S. H. C. de, Cojoianu, T., & Ascui, F. (2022). From impacts to dependencies: A first global assessment of corporate biodiversity risk exposure and responses. *Business Strategy and the Environment*, Article bse.3142. Advance online publication. https://doi.org/10.1002/bse.3142

Cavaco, S., Crifo, P., & Guidoux, A. (2020). Corporate social responsibility and governance: The role of executive compensation. *Industrial Relations: A Journal of Economy and Society*, *59*(2), 240–274. https://doi.org/10.1111/irel.12254

Chen, J [Joseph], Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345–381. https://doi.org/10.1016/S0304-405X(01)00066-6

Chen, J [Jun], Chan, K. C., Dong, W., & Zhang, F. (2017). Internal control and stock price crash risk: Evidence from China. *European Accounting Review*, *26*(1), 125–152. https://doi.org/10.1080/09638180.2015.1117008

Chiu, S.-C., & Sharfman, M. (2011). Legitimacy, visibility, and the antecedents of corporate social performance: An investigation of the instrumental perspective. *Journal of Management*, *37*(6), 1558–1585. https://doi.org/10.1177/0149206309347958

Christensen, D. M. (2016). Corporate accountability reporting and high-profile misconduct. *The Accounting Review*, *91*(2), 377–399. https://doi.org/10.2308/accr-51200

Dasgupta, P. (2021). *The economics of biodiversity: The Dasgupta review*. London.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, *7*(2), 197–226. https://doi.org/10.1016/0304-405X(79)90013-8

El Ghoul, S., Guedhami, O., Kim, H., & Park, K. (2018). Corporate environmental responsibility and the cost of capital: International evidence. *Journal of Business Ethics*, *149*(2), 335–361. https://doi.org/10.1007/s10551-015-3005-6

F&C Asset Management. (2004). *Is biodiversity a material risk for companies? An assessment of the exposure of FTSE sectors to biodiversity risk*. London.

Fiordelisi, F., Ricci, O., & Santilli, G. (2022). *Environmental engagement and stock price crash risk: Evidence from the European banking industry*. *SSRN Electronic Journal*.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, *13*(1), 15–36. https://doi.org/10.1146/annurev-financial-102620-103311

Godfrey, P. C., Merrill, C. B., & Hansen, J. M. (2009). The relationship between corporate social responsibility and shareholder value: An empirical test of the risk management hypothesis. *Strategic Management Journal*, *30*(4), 425–445. https://doi.org/10.1002/smj.750

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1-3), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002

Habib, A., Hasan, M. M., & Jiang, H. (2018). Stock price crash risk: Review of the empirical literature. *Accounting & Finance*, *58*, 211–251. https://doi.org/10.1111/acfi.12278

Hasan, M. M., Taylor, G., & Richardson, G. (2021). Brand capital and stock price crash risk. *Management Science*, Article mnsc.2021.4197. Advance online publication. https://doi.org/10.1287/mnsc.2021.4197

Hassan, A. M., Roberts, L., & Atkins, J. (2020). Exploring factors relating to extinction disclosures: What motivates companies to report on biodiversity and species protection? *Business Strategy and the Environment*, *29*(3), 1419–1436. https://doi.org/10.1002/bse.2442

Hassan, A. M., Roberts, L., & Rodger, K. (2022). Corporate accountability for biodiversity and species extinction: Evidence from organisations reporting on their impacts on nature. *Business Strategy and the Environment*, *31*(1), 326–352. https://doi.org/10.1002/bse.2890

Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies*, *33*(3), 1011–1023. https://doi.org/10.1093/rfs/hhz146

Hong, H. A., Kim, J.-B., & Welker, M. (2017). Divergence of cash flow and voting rights, opacity, and stock price crash risk: International evidence. *Journal of Accounting Research*, *55*(5), 1167–1212. https://doi.org/10.1111/1475-679X.12185

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, *94*(1), 67–86. https://doi.org/10.1016/j.jfineco.2008.10.003

IBPES. (2022). *Glossary: Ecosystem services*. https://ipbes.net/glossary/ecosystem-services

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Kennedy, S., Fuchs, M., Ingen, W., & Schoenmaker, D. (2022). A resilience approach to corporate biodiversity impact measurement. *Business Strategy and the Environment*, Article bse.3140. Advance online publication. https://doi.org/10.1002/bse.3140

Kim, J.-B., Li, X., Luo, Y., & Wang, K. (2020). Foreign investors, external monitoring, and stock price crash risk. *Journal of Accounting, Auditing & Finance*, *35*(4), 829–853. https://doi.org/10.1177/0148558X19843358

Kim, J.-B., Li, Y., & Zhang, L [Liandong] (2011). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, *100*(3), 639–662. https://doi.org/10.1016/j.jfineco.2010.07.007

Kim, J.-B., Si, Y., Xia, C., & Zhang, L [Lei] (2021). Corporate derivatives usage, information environment, and stock price crash risk. *European Accounting Review*, 1–35. https://doi.org/10.1080/09638180.2021.1918564

Kim, S.-H. (2015). Time to come clean? Disclosure and inspection policies for green production. *Operations Research*, *63*(1), 1–20. https://doi.org/10.1287/opre.2015.1345

Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, *43*, 1–13. https://doi.org/10.1016/j.jbankfin.2014.02.013

Kölbel, J., Leippold, M., Rillaerts, J., & Wang, Q. (2020). Does the CDS market reflect regulatory climate risk disclosures? *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.3616324

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Minnick, K., Lim, E., Bose, S., Shams, S., & Schorno, P. (2022). Does carbon risk influence stock price crash risk? International evidence. *SSRN Electronic Journal*.

Nedopil, C. (2022). Integrating biodiversity into financial decision-making: Challenges and four principles. *Business Strategy and the Environment*, Article bse.3208. Advance online publication. https://doi.org/10.1002/bse.3208

Rimmel, G., & Jonäll, K. (2013). Biodiversity reporting in Sweden: Corporate disclosure and preparers' views. *Accounting, Auditing & Accountability Journal*, *26*(5), 746–778. https://doi.org/10.1108/AAAJ-02-2013-1228

Schaltegger, S., Gibassier, D., & Maas, K. (2022). Managing and accounting for corporate biodiversity contributions. Mapping the field. *Business Strategy and the Environment*, Article bse.3166. Advance online publication. https://doi.org/10.1002/bse.3166

Schiemann, F., & Sakhel, A. (2019). Carbon disclosure, contextual factors, and information asymmetry: The case of physical risk reporting. *European Accounting Review*, *28*(4), 791–818. https://doi.org/10.1080/09638180.2018.1534600

Seltzer, L., Starks, L., & Zhu, Q. (2022). *Climate regulatory risk and corporate bonds* (National Bureau of Economic Research w29994). Cambridge, MA. https://www.nber.org/system/files/working_papers/w29994/w29994.pdf https://doi.org/10.3386/w29994

Silva, G. C., Regan, E. C., Pollard, E. H. B., & Addison, P. F. E. (2019). The evolution of corporate no net loss and net positive impact biodiversity commitments: Understanding appetite and addressing challenges. *Business Strategy and the Environment*, *28*(7), 1481–1495. https://doi.org/10.1002/bse.2379

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

Wagner, M. (2022). Business, biodiversity and ecosystem services: Evidence from large-scale survey data. *Business Strategy and the Environment*, Article bse.3141. Advance online publication. https://doi.org/10.1002/bse.3141

WEF. (2022). *The global risks report 2022.*

Yildiz, Y., & Karan, M. B. (2020). Environmental policies, national culture, and stock price crash risk: Evidence from renewable energy firms. *Business Strategy and the Environment*, *29*(6), 2374–2391. https://doi.org/10.1002/bse.2508

Zhang, X., Chan, K. C., & Tan, J. (2021). Environmental law enforcement as external monitoring: Evidence from the impact of an environmental inspection program on firm-level stock price crash risk. *International Review of Economics & Finance*, *71*, 21–31. https://doi.org/10.1016/j.iref.2020.08.020

Table 1: Variable description.

VARIABLES	DEFINITION
$\text{Biodiversity}_{i,t}$	Overall biodiversity management score, measured by the Vigeo Eiris ENV1.4 score.
$\text{Biodiversity Leadership}_{i,t}$	Score on biodiversity leadership, measured by the corresponding Vigeo Eiris ENV1.4 subscore.
$\text{Biodiversity Implementation}_{i,t}$	Performance regarding the implementation of measures aimed at the protection of biodiversity, measured by the corresponding Vigeo Eiris ENV1.4 subscore.
$\text{Biodiversity Results}_{i,t}$	Performance regarding stakeholder feedback related to biodiversity management, measured by the corresponding Vigeo Eiris ENV1.4 subscore.
$\text{DUOVOL}_{\text{i,t}}$	Negative conditional firm-specific weekly return skewness, defined as in Equation 3.
NCSKEW_{j}	Down to up volatility of firm-specific weekly returns, defined as in Equation 2.
LAGNCSKEW_{j}	Lagged value of NCSKEW.
SIGMA_{j}	Weekly return volatility, calculated as the standard deviation of weekly returns over the year.
$\text{RET}_{i,t}$	Weekly return, measured as the yearly mean of firm-specific weekly returns.
$\text{DTUNROVER}_{i,t}$	Change in monthly turnover, defined as the difference of average monthly share turnover between the current year and the previous year. Monthly share turnover is defined as the monthly trading volume divided by the total number of shares outstanding.
$\text{SIZE}_{i,t}$	Natural logarithm of market value of equity for firm *i* in year *t*.
$\text{MB}_{i,t}$	Market to book ratio, measured as the market value of equity divided by the book value of equity.
$\text{LEV}_{i,t}$	Leverage, defined as the total long-term debts divided by total assets.
$\text{ROA}_{i,t}$	Return on assets, defined as the income before extraordinary items divided by lagged total assets.
$\text{OPAQE}_{i,t}$	Firm opaqueness, measured as the prior three years' moving sum of the absolute value of discretionary accruals estimated by the model from Hutton et al. (2009).
$\text{ESG}_{i,t}$	The total Thomson Reuters ESG Refinitiv score for firm *i* in year *t*.

This table reports descriptions of the variables used in my analysis. The control variables are defined following J.-B. Kim et al. (2021). The subscripts i and t indicate firm- and year-specific variables.

Table 2: Sample Selection.

		Number of observations	Number of firms
	Biodiversity data	12,483	2,230
-	missing stock price data	142	14
-	missing control data	4,754	696
-	missing ESG data	426	118
=	Sample for baseline analysis	7,161	1,402
-	firms outside North America	5,740	1,037
=	Sample for difference-in-differences analysis	1,691	365

This table reports our sample selection procedure. We start with the whole universe for which Vigeo Eiris provides data on biodiversity management. Our sample period spans the years between 2009 and 2021.

Table 3: Sector and country distribution of companies included in the analysis

PANEL A: Sector distribution

Generic Sector	No.	%	Generic Sector	No.	%
Electric & Gas Utilities	189	13.48%	Building Materials	49	3.50%
Mining & Metals	147	10.49%	Financial Services - Real Estate	49	3.50%
Food	134	9.56%	Forest Products & Paper	37	2.64%
Pharmaceuticals & Biotechnology	134	9.56%	Industrial Goods & Services	35	2.50%
Energy	124	8.84%	Luxury Goods & Cosmetics	34	2.43%
Specialized Retail	112	7.99%	Chemicals	25	1.78%
Hotel, Leisure Goods & Services	70	4.99%	Waste & Water Utilities	17	1.21%
Supermarkets	57	4.07%	Tobacco	15	1.07%
Beverage	54	3.85%	Health Care Equipment & Services	11	0.78%
Heavy Construction	54	3.85%	Travel & Tourism	1	0.07%
Oil Equipment & Services	54	3.85%	Total	1,40	100.00%

PANEL B: Country Distribution

Country	No.	%	Country	No.	%
United States of America	257	18.33%	Malaysia	19	1.36%
Australia	115	8.20%	Sweden	19	1.36%
United Kingdom	114	8.13%	Mexico	18	1.28%
Canada	108	7.70%	New Zealand	16	1.14%
Japan	81	5.78%	Chile	15	1.07%
Hong Kong	64	4.56%	Indonesia	15	1.07%
China	48	3.42%	Norway	15	1.07%
South Korea	48	3.42%	Russia	15	1.07%
France	45	3.21%	Belgium	14	1.00%
India	38	2.71%	Denmark	13	0.93%
Italy	32	2.28%	Finland	13	0.93%
Brazil	31	2.21%	Peru	13	0.93%
Germany	31	2.21%	Poland	13	0.93%
Spain	27	1.93%	Portugal	10	0.71%
South Africa	24	1.71%	Singapore	10	0.71%
Taiwan	21	1.50%	Thailand	10	0.71%
Netherlands	20	1.43%	Other	50	3.57%
Switzerland	20	1.43%	Total	1,40	100.00%

This table gives an overview of our sample used for the baseline analysis. Panel A gives an overview of the industry distribution of the companies included in the baseline analysis using the Vigeo Eiris sector classification. Panel B gives an overview of the global distribution of the companies included in the baseline analysis by country of a company's headquarter. Both panels sorted by frequency. For brevity, we display all countries with less than 10 companies as single group (Other). Other includes Austria, Colombia, Czech Republic, Greece, Hungary, Ireland, Israel, the Philippines, Qatar, Turkey, and the United Arab Emirates. For our empirical analyses, we use country fixed effects for all countries, including those with less than 10 companies.

Table 4: Descriptive analysis.

VARIABLES	N	Median	Mean	Std. Dev.	P25	P75
Biodiversity	7,161	28.0000	31.7713	19.3809	14.0000	43.0000
Biodiv. Leadership	7,161	30.0000	31.5353	29.7860	0.0000	52.0000
Biodiv. Implementation	7,161	20.0000	27.3586	28.4442	0.0000	44.0000
Biodiv. Results	7,161	35.0000	36.2955	15.0913	28.0000	35.0000
DUVOL	7,161	0.1137	0.1151	0.7772	-0.3642	0.5923
NCSKEW	7,161	0.1116	0.1256	1.0385	-0.4545	0.6751
LAGNCSKEW	7,161	0.1200	0.1555	0.9485	-0.4356	0.6779
SIGMA	7,161	0.0419	0.0477	0.0237	0.0311	0.0577
RET	7,161	0.1398	0.1361	0.6347	-0.2309	0.5043
DTURNOVER	7,161	0.0000	0.0010	0.0338	-0.0094	0.0098
SIZE	7,161	8.8110	8.8537	1.3873	7.9293	9.7411
MB	7,161	1.8200	2.8646	3.8380	1.1100	3.2100
LEV	7,161	0.2198	0.2313	0.1519	0.1229	0.3235
ROA	7,161	0.0416	0.0512	0.0771	0.0165	0.0810
OPAQUE	7,161	0.7897	0.6464	0.4146	0.5609	0.9064
ESG	7,161	58.9600	56.8385	19.4279	43.6700	72.1100

This table reports the summary statistics of the variables deployed in the baseline analysis. We winsorize all control variables at the 1 percent and 99 percent level.

Table 5: Correlation analysis.

	VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Biodiversity	1.00															
(2)	Biodiv. Leadership	0.88*	1.00														
(3)	Biodiv. Implementation	0.88*	0.64*	1.00													
(4)	Biodiv. Results	0.47*	0.20*	0.22*	1.00												
(5)	DUVOL	-0.02	-0.02*	-0.01	-0.02	1.00											
(6)	NCSKEW	-0.02	-0.02	-0.01	-0.02	0.92*	1.00										
(7)	LAGNCSKEW	-0.05*	-0.04*	-0.03*	-0.03*	-0.01	0.00	1.00									
(8)	SIGMA	-0.02	-0.04*	-0.03*	0.06*	-0.09*	-0.09*	-0.08*	1.00								
(9)	RET	0.03*	0.03*	0.03*	0.00	0.08*	0.06*	-0.49*	0.03*	1.00							
(10)	DTURNOVER	-0.02*	-0.02	-0.02*	0.00	-0.03*	-0.03*	0.04*	0.29*	-0.07*	1.00						
(11)	SIZE	0.28*	0.29*	0.31*	-0.06*	0.08*	0.07*	0.03*	-0.39*	-0.01	-0.05*	1.00					
(12)	MB	0.03*	0.04*	0.03*	-0.01	-0.02	-0.01	-0.01	0.07*	-0.01	0.00	-0.04*	1.00				
(13)	LEV	0.04*	0.05*	0.03*	0.02	0.00	0.00	0.02*	-0.01	-0.04*	0.05*	0.04*	-0.05*	1.00			
(14)	ROA	0.03*	0.03*	0.03*	-0.01	-0.02	-0.02	-0.09*	-0.14*	0.21*	-0.05*	0.20*	-0.03*	-0.17*	1.00		
(15)	OPAQUE	-0.04*	-0.04*	-0.04*	-0.01	0.01	0.02	0.01	-0.12*	0.00	-0.02	0.01	0.01	0.04*	0.04*	1.00	
(16)	ESG	0.51*	0.50*	0.48*	0.08*	-0.01	0.01	0.01	-0.12*	0.02	-0.01	0.43*	0.02	0.05*	0.07*	-0.03*	1.00

This table reports the pairwise correlation coefficients of the variables deployed in the baseline analysis. Significance at the 5% level is indicated by *.

Table 6: DUVOL regression analysis.

VARIABLES	(1) DUVOL	(2) DUVOL	(3) DUVOL	(4) DUVOL
Biodiversity	-0.0017***			
	(0.0006)			
Biodiv. Leadership		-0.0010**		
		(0.0004)		
Biodiv. Implementation			-0.0011***	
			(0.0004)	
Biodiv. Results				-0.0001
				(0.0006)
LAGNCSKEW	0.0229*	0.0233*	0.0232*	0.0242*
	(0.0128)	(0.0128)	(0.0128)	(0.0129)
SIGMA	-2.2474***	-2.2501***	-2.2515***	-2.2632***
	(0.6766)	(0.6767)	(0.6771)	(0.6772)
RET	0.1379***	0.1384***	0.1382***	0.1390***
	(0.0200)	(0.0200)	(0.0200)	(0.0200)
DTURNOVER	-0.0624	-0.0692	-0.0571	-0.0618
	(0.3386)	(0.3387)	(0.3388)	(0.3389)
SIZE	0.0332***	0.0323***	0.0342***	0.0284***
	(0.0101)	(0.0101)	(0.0101)	(0.0100)
MB	0.0036	0.0036	0.0035	0.0036
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
LEV	-0.0778	-0.0788	-0.0821	-0.0825
	(0.0695)	(0.0695)	(0.0694)	(0.0691)
ROA	0.5470***	0.5445***	0.5443***	0.5580***
	(0.1637)	(0.1636)	(0.1636)	(0.1632)
OPAQUE	0.0021	0.0017	0.0025	0.0025
	(0.0224)	(0.0223)	(0.0224)	(0.0224)
ESG	-0.0007	-0.0007	-0.0008	-0.0013**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Constant	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	7,161	7,161	7,161	7,161
Adjusted R-squared	0.0361	0.036	0.036	0.0352

This table reports the results of an OLS estimation of Equation 4, regressing the Biodiversity score on DUVOL as one of two different measures of stock price crash risk. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors clustered at the firm level in parentheses below each coefficient. We winsorize all control variables at the 1 percent and 99 percent level.

Table 7: NCSKEW regression analysis.

VARIABLES	(1) NCSKEW	(2) NCSKEW	(3) NCSKEW	(4) NCSKEW
Biodiversity	-0.0027***			
	(0.0008)			
Biodiv. Leadership		-0.0015***		
		(0.0005)		
Biodiv. Implementation			-0.0016***	
			(0.0005)	
Biodiv. Results				-0.0005
				(0.0008)
LAGNCSKEW	0.0314*	0.0319*	0.0320*	0.0333*
	(0.0183)	(0.0182)	(0.0183)	(0.0183)
SIGMA	-3.0135***	-3.0173***	-3.0214***	-3.0371***
	(0.9215)	(0.9229)	(0.9216)	(0.9236)
RET	0.1644***	0.1653***	0.1651***	0.1660***
	(0.0273)	(0.0272)	(0.0273)	(0.0273)
DTURNOVER	-0.1147	-0.1254	-0.1071	-0.1129
	(0.4359)	(0.4363)	(0.4364)	(0.4363)
SIZE	0.0343**	0.0330**	0.0352***	0.0267**
	(0.0133)	(0.0134)	(0.0133)	(0.0133)
MB	0.0021	0.0021	0.002	0.0022
	(0.0039)	(0.0039)	(0.0039)	(0.0039)
LEV	-0.0227	-0.0243	-0.0296	-0.029
	(0.0937)	(0.0936)	(0.0935)	(0.0933)
ROA	0.5786**	0.5744**	0.5761**	0.5973***
	(0.2298)	(0.2301)	(0.2300)	(0.2301)
OPAQUE	0.0059	0.0053	0.0066	0.0065
	(0.0286)	(0.0285)	(0.0287)	(0.0287)
ESG	0.0002	0.0001	0.0000	-0.0006
	(0.0009)	(0.0009)	(0.0009)	(0.0008)
Constant	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	7,161	7,161	7,161	7,161
Adjusted R-squared	0.0286	0.0285	0.0283	0.0273

This table reports the results of an OLS estimation of Equation 4, regressing the Biodiversity score on NCSKEW as one of two different measures of stock price crash risk. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors clustered at the firm level in parentheses below each coefficient. We winsorize all control variables at the 1 percent and 99 percent level.

Table 8: Interaction analysis.

VARIABLES	(1) DUVOL	(2) NCSKEW	(3) DUVOL	(4) NCSKEW	(5) DUVOL	(6) NCSKEW	(7) DUVOL	(8) NCSKEW
Biodiv. Results (X)	0.0002	0.0000	0.0005	0.0003	0.0004	0.0001	0.0004	0.0004
	(0.0007)	(0.0009)	(0.0006)	(0.0009)	(0.0006)	(0.0009)	(0.0007)	(0.0009)
Biodiv. Leadership	-0.0012**	-0.0016**						
	(0.0005)	(0.0007)						
Biodiv. Implementation			-0.0016***	-0.0022***				
			(0.0005)	(0.0007)				
Interaction term (below median)								
X * Low Biodiv. Leadership	-0.0004	-0.0002						
	(0.0007)	(0.0010)						
X * Low Biodiv. Implementation			-0.0009	-0.001				
			(0.0008)	(0.0010)				
X * Low ROA					-0.0013**	-0.0014*		
					(0.0006)	(0.0008)		
X * Low ESG							-0.0017**	-0.0025**
							(0.0008)	(0.0011)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,161	7,161	7,161	7,161	7,161	7,161	7,161	7,161
Adjusted R-squared	0.0358	0.0282	0.036	0.0282	0.0356	0.0276	0.0357	0.0281

This table reports the results of an OLS estimation, regressing the score capturing stakeholder feedback on biodiversity management on DUVOL and NCSKEW as our two different measures of stock price crash risk. We add interaction terms between the Biodiversity Results score and several dummy variables. We assign the dummy variable (i.e., Low Biodiv. Leadership) a value of one if the value of a firm-year observation (i.e., in terms of Biodiv. Leadership) is smaller than the median value of this variable in our whole sample, and zero otherwise. We include all control variables used in the main regression (Table 6 and Table 7). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors clustered at the firm level in parentheses below each coefficient. We winsorize all control variables at the 1 percent and 99 percent level.

Table 9: Environmental inspection subsample descriptive analysis.

	Treatment Group		Control Group		
VARIABLES	N	Mean	N	Mean	Diff
DUVOL	57	0.3671	57	0.4103	-0.0432
NCSKEW	57	0.4355	57	0.4448	-0.0092
LAGNCSKEW	57	0.4773	57	0.2604	0.2169
SIGMA	57	0.031	57	0.0388	-0.0077***
RET	57	0.0782	57	0.0985	-0.0203
DTURNOVER	57	-0.0056	57	0.0006	-0.0062
SIZE	57	10.0193	57	9.3377	0.6816***
MB	57	3.7768	57	3.3574	0.4195
LEV	57	0.3037	57	0.3035	0.0002
ROA	57	0.0791	57	0.0661	0.013
OPAQUE	57	0.5852	57	0.7467	-0.1615**
ESG	57	61.9253	57	47.013	14.9123***

This table provides a summary of the variables used in the difference-indifferences regression for both treatment and control firms one year prior to the respective merger. Firms are assigned to the treatment group if their facilities are subject to an inspection by the US environmental protection agency (EPA). The potential control group consists of all firms that had no inspection during the entire sample period. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 10: Environmental inspection subsample difference-in-differences analysis.

VARIABLES	(1) NCSKEW	(2) DUVOL
Post	-0.4779**	-0.3681**
	(0.2241)	(0.1506)
Treat*Post	0.4481*	0.3352*
	(0.2682)	(0.1810)
Treat	-0.0629	-0.0717
	(0.2011)	(0.1413)
Constant	Yes	Yes
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	301	301
Adjusted R-squared	0.0742	0.1199

This table reports the results of a difference-in-differences estimation using a propensity score matched sample. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Robust standard errors are reported in parentheses below each coefficient. We winsorize all control variables at the 1 percent and 99 percent level.

Table 11: High-risk industries analysis.

VARIABLES	(1) DUVOL	(2) NCSKEW	(3) DUVOL	(4) NCSKEW	(5) DUVOL	(6) NCSKEW	(7) DUVOL	(8) NCSKEW
High Risk	0.0736	0.1161	0.0939	0.129	0.0991	0.1348	0.0798	0.1301
	(0.1003)	(0.1254)	(0.0972)	(0.1213)	(0.0954)	(0.1187)	(0.1066)	(0.1329)
Biodiversity	-0.0027***	-0.0036***						
	(0.0008)	(0.0011)						
Biodiv. Leadership			-0.0015***	-0.0020**				
			(0.0006)	(0.0008)				
Biodiv. Implementation					-0.0020***	-0.0025***		
					(0.0005)	(0.0008)		
Biodiv. Results							-0.0007	-0.0008
							(0.0009)	(0.0013)
Interaction term (high risk industry)								
High Risk * Biodiversity	0.0018*	0.0017						
	(0.0010)	(0.0014)						
High Risk * Biodiv. Leadership			0.0008	0.0008				
			(0.0007)	(0.0009)				
High Risk * Biodiv. Implementation					0.0016**	0.0017*		
					(0.0007)	(0.0010)		
High Risk * Biodiv. Results							0.001	0.0006
							(0.0013)	(0.0017)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,161	7,161	7,161	7,161	7,161	7,161	7,161	7,161
Adjusted R-squared	0.0364	0.0287	0.0361	0.0284	0.0365	0.0286	0.0351	0.0272

This table reports the results of an OLS estimation, regressing our measures of biodiversity management on our two different measures of stock price crash risk, DUVOL and NCSKEW. We add interaction terms between the biodiversity management (sub)scores and a dummy variable indicating sectors at high risk regarding biodiversity loss. We assign the dummy variable a value of one if the company is active in a red zone sector, defined by F&C Asset Management (2004), and zero otherwise. We include all control variables used in the main regression (Table 6 and Table 7). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors clustered at the firm level in parentheses below each coefficient. We winsorize all control variables at the 1 percent and 99 percent level.